

Size/Layout Optimization of Truss Structures Using Vibrating Particles System Meta-heuristic Algorithm and its Improved Version

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Abstract

Vibrating Particles System (VPS) optimization is a newly made meta-heuristic algorithm to optimize problems by inspiration of the free vibration of viscous-damped systems with single degree of freedom. The agents are modeled as particles which systematically proceed toward their equilibrium conditions that are reached by the existing population and historically best position. To enhance the performance of the VPS algorithm, Enhanced Vibrating Particles System (EVPS) applies a new process for updating agent's positions. This paper tries to improve the EVPS algorithm with the aim of reduction in the regulatory parameters' effect on the algorithm's performance by reducing the regulatory parameters. To evaluate the performance of the proposed method, it is applied to four optimization problems of truss structures including mixed of discrete and continuous design search spaces with displacement, stress and buckling constraints. As a result, the proposed algorithm is a suitable method and more research can be done on it.

Keywords

meta-heuristic algorithms, vibrating particles system algorithm, improved vibrating particles system algorithm, truss optimization, sizing and layout optimization

1 Introduction

The term "optimization" means the systematic selection of values for variables from or within a permissible collection, seeking to minimize or maximize the function of a problem [1]. One of the optimization tools is meta-heuristic algorithms that are able to achieve a global or near-global optimal solutions by spending the right amount of time. Some of these algorithms are listed as follows: Particle Swarm Optimization (PSO) [2], Genetic Algorithms (GA) [3], Colliding Bodies Optimization (CBO) [4], Ant Colony Optimization (ACO) [5], Charged System Search algorithm (CSS) [6], Harmony Search (HS) [7], Simulated Annealing (SA) [8], Ray Optimization (RO) [9], Big-Bang Big-Crunch (BBBC) [10], and Vibrating Particles System (VPS) [11].

Researchers in recent years have sought to develop the field of structural optimization by optimizing ideal small structural systems and components to enable the optimal design of more intricate structures [12]. Structural optimization is classified into three kinds: (1) Optimizing the size of sections (2) Optimizing the shape of the structure (3) Optimization of structural topology [13]. Truss

structure is one of the most useful civil engineering structures in around the world. Truss optimization has been considered by engineers and researchers for decades [14]. Therefore, truss structures are suitable tool to evaluate the performance of optimization algorithms. Size/layout optimization expresses minimizing the weight of the structure by selecting cross-sections and configuration of the structural members under strength constraints and serviceability limits. Different meta-heuristic algorithms have been used by various researchers to optimize the size and layout of the structure. For instance, Wu and Chow [15] considered the sections and nodal coordinates as a discrete and continuous variables to optimize space trusses by GA algorithm, Hasańcebi and Erbatur [16] used "annealing perturbation" and "adaptive reduction of the design space" method to improve GA for mass minimization of space trusses, Hasańcebi and Erbatur [17] used Simulated Annealing (SA) algorithm, Kaveh and Kalatjari [18] used the force method and genetic algorithm to minimize the weight of the truss structure, Tang et al. [19] optimized size,

shape and topology of trusses using the improved Genetic Algorithm (GA), Rahami et al. [20] employed energy and force method and Genetic algorithm (GA) for optimize the size and layout of the truss structures, Kazemzadeh Azad et al. [21] suggested a Mutation-Based Real-Coded Genetic Algorithm (MBRCGA) for minimizing the weight of truss, Miguel et al. [22] presented a single-stage Firefly-based Algorithm (FA) to study simultaneous size, shape and topology optimization for trusses, Gholizadeh [23] proposed a hybrid of Cellular Automata (CA) and the Particle Swarm Optimization (PSO) algorithm to solve size and layout optimization of truss structures, Mortazavi et al. [24] utilized integrated Particle Swarm Optimizer (iPSO) algorithm for sizing and shape optimization of planar and spatial truss structures, Panagant and Bureerat [25] suggested Fully Stressed Design-Grey Wolf-Adaptive Differential Evolution (FSD-GWADE), Kaveh and Zaezreza [13] utilized shuffled shepherd optimization algorithm (SSOA), Jawad et al. [26] used Artificial Bee Colony (ABC) algorithm, Kaveh et al. [27] studied layout optimization of planar braced frames by using Colliding Bodies Optimization (CBO) and Colliding Bodies Optimization-Modified Dolphin Monitoring (CBO-MDM).

Vibrating Particles System (VPS) is a multi agent-based randomly optimization algorithm by inspiration of the free vibration of viscous-damped systems with single degree of freedom where particles move toward minimum energy level [11]. The high number of regulatory parameters is one of the features of VPS that affect the performance of the algorithm. Therefore to reduce the impact of these regulatory parameters on the algorithm's performance, in present study, in addition to applying a new process for update the particles position provided by Kaveh et al. [28], by Weighing of regulatory parameters based on the objective function values and adding a mutation mechanism to escape from local optima, standard VPS is improved to formulate the IVPS (Improved Vibrating Particles System) algorithm. The ability of the proposed method are compared to those standard and enhanced version of the vibrating particle system algorithm and some other powerful metaheuristic algorithms on some size/layout optimization of truss structure problems. Results indicate that the proposed method is a promising development to improve the performance of the standard version of the VPS algorithm.

The present paper consists of six sections. After this introduction as the Section 1, in Section 2, the mathematical formulations of sizing-layout truss structural optimization are stated. In Section 3 the vibrating particles system algorithm and its enhanced version is briefly described.

The proposed method is explained in Section 4. Four well know sizing and shape optimization of truss structures are studied in Section 5. Finally, conclusions are presented in Section 6.

2 Formulation of the structural optimization problems

In the present study, the aim is to optimize size and layout of the truss structures while satisfying under some design constraints to achieve the minimum weight of the structure. Two types of design variables (a) cross sections areas for elements of truss and (b) coordinates of some joints of truss are organized to minimize the weight of truss structures in size and layout optimization. To optimize the size and shape to achieve the lowest weight of the truss structure, the objective function is expressed as follows:

$$\begin{aligned} \text{Find } \{X\} &= [x_1, x_2, \dots, x_{ng}, x_{ng+1}, x_{ng+2}, \dots, x_{ng+nm}], \\ \text{To minimize } W(\{X\}) &= \sum_{i=1}^{nm} \rho_i A_i L_i, \\ \text{Subjected to } &\begin{cases} g_j(\{X\}) \leq 0, j = 1, 2, \dots, nc \\ x_{\min} \leq x_i \leq x_{\max} \end{cases}. \end{aligned} \quad (1)$$

Where $\{X\}$ is a vector of optimization variables comprising the cross-sectional areas and the coordinates of some nodes; ng is the number of member groups for cross-sectional area; nm is the number of nodes should be set those coordinates; $W(\{X\})$ presents the weight of the structure; nm is the number of elements of the structure; nc is the number of constraints; ρ_i presents the material density of i th member; A_i and L_i denote the cross-section area and the length of the i th member, respectively. x_{\min} and x_{\max} are the minimum and the maximum allowable values of optimization variables in the search space. $g_j(\{X\})$ presents design constraints; and nc is the number of constraints.

For handling the different constraints in optimization problems of this paper, a penalty approach is used. So, the objective function (Eq. (1)) is redefined as follows:

$$P(\{X\}) = (1 + \varepsilon_1 \cdot v)^{\varepsilon_2} \times W(\{X\}). \quad (2)$$

Where $P(\{X\})$ presents the penalized objective function that should be minimized, v is the sum of the violations of the design constraints. Here, ε_1 is considered as unity and ε_2 is determined by:

$$\varepsilon_2 = 1.5 + 1.5 \times \frac{iter}{iter_{\max}}, \quad (3)$$

where $iter$ is the current iteration number and $iter_{\max}$ is the maximum iteration number.

3 Vibrating particles system algorithm

In this section the phenomenon of damped free vibration, the VPS algorithm, the VPS algorithm and the EVPS algorithm are presented briefly.

3.1 The damped free vibration phenomenon

Vibration means the reciprocating motion of a particle around its equilibrium position. If the vibration is out of the system due to the presence of periodic force (displacement or velocity), it is called forced vibration, and if it is due to the internal forces of the system, it is called free vibration. A body with mass of m as the vibrating particle, a spring with hardness of k that acts as the inertial force of the system, and a viscous damper with viscous damping coefficient of c that simulates energy loss during vibration (Fig. 1) have been used to modeling the free vibration of viscous-damped systems with single degree of freedom. The motion equation of the body when it shifts as far as x relative to its equilibrium position will be as follows:

$$m\ddot{x} + c\dot{x} + kx = 0. \quad (4)$$

Two parameters of the damping ratio ξ and the critical damping coefficient c_c are defined to solve this differential equation as follows:

$$\xi = \frac{c}{c_c}, \quad (5)$$

$$c_c = 2m\omega_n, \quad (6)$$

$$\omega_n = \sqrt{\frac{k}{m}}, \quad (7)$$

where ω_n is the natural circular frequency of the system.

Depending on the value of the damping ratio ξ , can be divided into three different types of systems: (1) over-damped system ($\xi > 1$); (2) critically damped system ($\xi = 1$) and (3) under-damped system ($\xi < 1$). A particle only has intermittent motion around its equilibrium position when $\xi < 1$ (under-damped system). In this case, the solution of Eq. (4) is as follows:

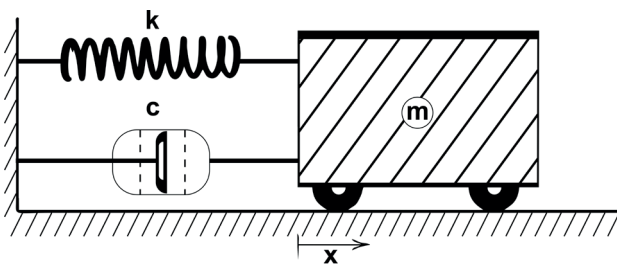


Fig. 1 Viscous-damped free vibration

$$x(t) = \rho e^{-\xi\omega_n t} \sin(\omega_D t + \phi), \quad (8)$$

$$\omega_D = \omega_n \sqrt{1 - \xi^2}, \quad (9)$$

where ρ and ϕ are constants and respect to the initial conditions of the system are calculated. ω_D and t are damped natural frequency of the system and time, respectively.

3.2 The VPS algorithm

In this algorithm, the initial position of the particles is randomly generated in the search space by:

$$x_i^j = x_{\min} + rand \cdot (x_{\max} - x_{\min}), \quad (10)$$

where x_i^j is the j th variable of i th particle; $rand$ is a random number uniformly distributed in the range of $[0, 1]$.

After calculating the objective function of each particle, three particles HB, GP and BP are used to update the position of the particles, which are the best position from the historically of the whole particle population, good particle and bad particle, respectively. To determine GP and BP, at the first the particle population are sorted in ascending order based on their objective function values, and each of the GP and BP particles is randomly selected from the upper and lower halves, respectively. The following formula is then used to update the particle position:

$$x_i^j = \omega_1 \cdot [D \cdot A \cdot rand1 + HB^j] + \omega_2 \cdot [D \cdot A \cdot rand2 + GP^j] + \omega_3 \cdot [D \cdot A \cdot rand3 + BP^j], \quad (11)$$

$$A = [\omega_1 \cdot (HB^j - x_i^j)] + [\omega_2 \cdot (GP^j - x_i^j)] + [\omega_3 \cdot (BP^j - x_i^j)], \quad (12)$$

$$D = \left(\frac{iter}{iter_{\max}} \right)^{-\alpha}, \quad (13)$$

$$\omega_1 + \omega_2 + \omega_3 = 1. \quad (14)$$

Where A and D simulates amplitude of vibration and damping, respectively. α is a constant; ω_1 , ω_2 , and ω_3 are three parameters to measure the relative importance of HB, GP, and BP, respectively. $rand1$, $rand2$, and $rand3$ are random numbers uniformly distributed in the range of $[0, 1]$.

The VPS algorithm is one of the swarm intelligence algorithms that tries to update the position of particles by learning from the existing particle positions. This algorithm obtains the new position of the particles using vibration around three equilibrium positions HB, GP and BP. Moving towards the HB and GP particles provides exploitation phase of the algorithm so that the new

position of the particle approaches the position of the particle with a better objective function. On the other hand, moving towards the BP particle avoids the algorithm being in local optima, and provides exploration phase for the algorithm. Using the combination of these three particles in updating the particle position creates a balance between the exploitation and exploration phases of the algorithm. The probability of the impact of each of the HB, GP and BP particles in updating the new position of particle is controlled using the parameters ω_1 , ω_2 and ω_3 . Inspired by Eq. (8), Eq. (11) tries to search randomly in the solution space by vibration around three equilibrium positions HB, GP and BP. For this purpose, A (Eq. (12)) simulates the amplitude of the particle oscillation, just like the ρ parameter in Eq. (8), and D (Eq. (13)) simulates the term $e^{-\xi_{cont}}$ in Eq. (8) which represents the damping property by reducing the amplitude of particle motion and causes the answers to converge to an optimal solution, while increasing the iteration loops of the algorithm. Also, in Eq. (11) the value of $\sin(\omega_D t + \phi)$ is considered unity to have vibration with maximum amplitude.

To decide whether the effect of BP should be considered in the updating process of particle position or not, the parameter p is generated between 0 and 1. For this purpose, if $p < rand$, then $\omega_3 = 0$ and $\omega_2 = 1 - \omega_1$.

To avoid of boundary violation when the particle position is being updated, the harmony search-based side constraint handling approach is used [29]. In this method, the violating component should be changed with the corresponding component of the historically best position of a random particle with the possibility like Harmony Memory Considering Rate (HMCR) parameter, otherwise it must be regenerated from the permissible search space. Moreover, if it is replaced by the component of a historically best position, this value should be changed with the neighboring value by the possibility like Pitch Adjusting Rate (PAR).

3.3 The EVPS algorithm

In this section, the Enhanced Vibration Particle System (EVPS) algorithm that presented by Kaveh and Hoseini Vaez [28] is briefly described.

In the EVPS algorithm, A parameter like Memory is defined that it saves NB number of the historically best positions in the whole population. On the other hand, HB is replaced with OHB (one of the historically best positions in the whole population) that it is one row of Memory. The best answer for each iteration is compared with the worst value of the Memory, to be replaced if it is better.

The change in the mechanism of updating the position of the particles is another change made in this method. According to that, one of the (a), (b) and (c) from Eq. (15) is used with the possibility of ω_1 , ω_2 , and ω_3 , respectively instead Eq. (11).

$$x_i^j = \begin{cases} \left[D.Arand1 + OHB^j \right]; (a) \\ \left[D.Arand2 + GP^j \right]; (b) , \\ \left[D.Arand3 + BP^j \right]; (c) \end{cases} \quad (15)$$

$$A = \begin{cases} \pm 1(OHB^j - x_i^j); (a) \\ \pm 1(GP^j - x_i^j); (b) , \\ \pm 1(BP^j - x_i^j); (c) \end{cases}$$

where (± 1) are used randomly. OHB, GP and BP are determined independently for each particle.

4 Presentation of present method

In this section, the present method is introduced. In the continuation of changes made by Kaveh and Hoseini Vaez [28], corrections will be made to reduce the number of regulatory parameters in the process of the algorithm. These amendments are as follows:

In this method, instead of assigning specific numbers to the parameters ω_1 , ω_2 , and ω_3 , the values are assigned relative to the evaluated objective function of OHB, GP, and BP particles, respectively. Therefore, in order to create a new position for a selected particle (i th particle), the following can be done:

Step 1: The initial weights for the four particles OHB, GP, BP and the selected particle are calculated with Eq. (16), Eq. (17), Eq. (18) and Eq. (19), respectively. In these equations, the objective function is considered as a minimization function.

$$m_{OHB} = \frac{1}{Cost_{OHB}}, \quad (16)$$

$$m_{GP} = \frac{1}{Cost_{GP}}, \quad (17)$$

$$m_{BP} = \frac{1}{Cost_{BP}}, \quad (18)$$

$$m_{IP} = \frac{1}{Cost_{IP}}, \quad (19)$$

where m_{OHB} , m_{GP} , m_{BP} and m_{IP} are the initial weights assigned to the OHB, GP, BP and selected particle,

respectively; $Cost_{OHB}$, $Cost_{GP}$, $Cost_{BP}$ and $Cost_{IP}$ are the objective function values that are calculated for the OHB, GP, BP and selected particle, respectively.

Step 2: According to Eqs. (20) and (21), two key ranks d_1 and d_2 are defined, respectively. The rank of the selected particle in the list which the particles are sorted in ascending order based on their objective function values (the objective function is considered as a minimization function) is compared by two key ranks d_1 and d_2 . Then, based on the following conditions, the weight of the selected particle (m_{IP}) is assigned to the initial weight of one of the three particles OHB, GP and BP:

- If the rank of the selected particle in the ordered list is less than d_1 , according to Eq. (22), the weight of selected particle will be added to the initial weight of the OHB.
- If the rank of the selected particle in the ordered list is more than d_2 , according to Eq. (23), the weight of selected particle will be added to the initial weight of the GP.
- Otherwise, according to Eq. (24), the weight of selected particle will be added to the initial weight of the BP.

$$d_1 = \frac{PopulationSize \times \gamma}{4}, \quad (20)$$

$$d_2 = \frac{PopulationSize}{2}, \quad (21)$$

$$m_{OHB}^{new} = (m_{OHB} + m_{IP}) \times \beta \quad (22)$$

$$m_{GP}^{new} = (m_{GP} + m_{IP}) \times \beta \quad (23)$$

$$m_{BP}^{new} = (m_{BP} + m_{IP}) \times \gamma, \quad (24)$$

Where $PopulationSize$ is all candidate solutions; m_{OHB}^{new} , m_{GP}^{new} and m_{BP}^{new} are the new weights calculated for particles OHB, GP and BP, respectively. To satisfy the balance between the two phases of exploitation and exploration during the increase in number of iterations of the algorithm, we create γ and β according to Eq. (25) and Eq. (26) as the decremental and incremental parameters, respectively which lead to more exploration-less exploitation in the initial iteration loops of the algorithm and less exploration-more exploitation in the final iteration loops of the algorithm.

$$\gamma = \frac{iter_{max} - iter}{iter_{max}} \quad (25)$$

$$\beta = \frac{iter_{max} + iter}{iter_{max}} \quad (26)$$

According to the second step, in the initial iteration loops of the algorithm, the effect of good and bad particles decreases and increases, respectively, and in the final iteration loops of the algorithm, the effect of good and bad particles increases and decreases, respectively. Also, by adding the weight of the selected particle (m_{IP}) to the weight of the OHB particle (m_{OHB}), the convergence speed is increased, and to avoid being in the local optima, we reduce the probability of this effect by considering the γ reduction coefficient.

Step 3: Finally, the parameters ω_1 , ω_2 and ω_3 which are the three parameters for measuring the relative importance of OHB, GP and BP are equal to the ratio of the new weight of the OHB, GP and BP particles to the total new weight of these three particles, respectively (according to Eq. (27), Eq. (28) and Eq. (29)).

$$(27)$$

$$\omega_1 = \frac{m_{OHB}^{new}}{m_{OHB}^{new} + m_{GP}^{new} + m_{BP}^{new}}; (\omega_1 \text{ is relative importance to OHB})$$

$$(28)$$

$$\omega_2 = \frac{m_{GP}^{new}}{m_{OHB}^{new} + m_{GP}^{new} + m_{BP}^{new}}; (\omega_2 \text{ is relative importance to GP})$$

$$(29)$$

$$\omega_3 = \frac{m_{BP}^{new}}{m_{OHB}^{new} + m_{GP}^{new} + m_{BP}^{new}}; (\omega_3 \text{ is relative importance to BP})$$

Further, in this version of the algorithm, the regulatory parameter p has been removed from the EVPS algorithm. Also, to avoid being in the local optima, a mechanism such as the mutation mechanism in the Genetic Algorithm (GA) and then a new parameter μ_0 has been added to the algorithm. According to Eq. (30), the parameter μ is obtained based on μ_0 and this parameter is compared with $rand$. If $\mu > rand$, the position of the j th variable from the particle according to the Eq. (10) is reproduced within the design range. In the initial iteration loops of the algorithm, μ parameter is equal to μ_0 and with increasing iterations, this parameter decreases to zero.

$$\mu = \mu_0 \times \gamma, \quad (30)$$

where μ_0 is the mutation rate that is set in the range of [0,1].

5 Numerical examples

The performance and applicability of the present method is assessed by four sizing and layout optimization problems and its performance is compared with other versions of VPS algorithm. The parameter of the maximum number of iterations are 500 for the first three problems and 1500 for the

fourth problem. The number of population for all problems is 20. Other parameters for VPS and EVPS algorithms (including α , p , ω_1 , ω_2 , NB, HMCR, PAR and neighbor) are set based on [11] and [30], respectively. It should be noted that in the references the value of 0.7 is suggested for the p parameter of VPS algorithm, but in this research, two values of 0.2 and 0.7 have been considered for the mentioned parameter, and the best result for one of these two values is presented in the tables. Also, the MATLAB code provided in [30–32] are used for the EVPS algorithm, the 2017 and 2019 versions of the VPS algorithm, respectively. Thirty independent optimization runs are carried out for each example.

5.1 The planar 15-bar truss structure

The 15-bar planar truss structure is the first example to be considered. This truss is affected by a force of 10 kips as shown in Fig. 2. This example consists of 23 variables that 15 of them are in discrete search space for sizing optimization and the rest are in continuous search space for layout optimization. Information about modeling and optimization are presented in Table 1.

Table 2 shows that the present method obtains acceptable results compared to other algorithms. Although MBRCGA [21], SCPSO [23] and iPSO [24] algorithms have better results than the present method, but the best weight obtained by the present method compared to the VPS algorithm and its enhanced version (EVPS) is better, but the number of analyzes that the present method needs to achieve the best weight is more than the other two versions. Fig. 3 shows the best shape for the 15-bar truss obtained by the present method. Fig. 4 shows a comparison between the convergence history of VPS, EVPS algorithms and the present method for the average performance of the algorithms in 30 independent runs. The convergence history of the present method for the mean and best performance of the algorithm in 30 independent runs are shown in Fig. 5.

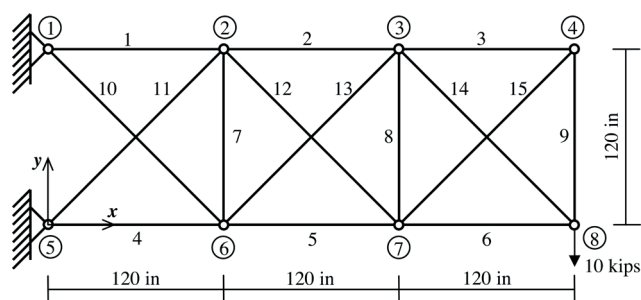


Fig. 2 Schematic of the 15-bar planar truss

Table 1 Modeling and design data for the 15-bar planar truss

Simulation and design data	
Design variables:	
Sizing variables	$A_i, i = 1, 2, \dots, 15.$
Layout variables	$x_2 = x_6; x_3 = x_7; y_2; y_3; y_4; y_6; y_7; y_8.$
Search range:	
Possible sizing variables	$A_i \in S = \{0.111, 0.141, 0.174, 0.220, 0.270, 0.287, 0.347, 0.440, 0.539, 0.954, 1.081, 1.174, 1.333, 1.488, 1.764, 2.142, 2.697, 2.800, 3.131, 3.565, 3.813, 4.805, 5.952, 6.572, 7.192, 8.525, 9.300, 10.850, 13.330, 14.290, 17.170, 19.180\} (in^2).$
Layout variables bounds	$100 \text{ in.} \leq x_2 \leq 140 \text{ in.}; 220 \text{ in.} \leq x_3 \leq 260 \text{ in.};$ $100 \text{ in.} \leq y_2 \leq 140 \text{ in.}; 100 \text{ in.} \leq y_3 \leq 140 \text{ in.};$ $50 \text{ in.} \leq y_4 \leq 90 \text{ in.}; -20 \text{ in.} \leq y_6 \leq 20 \text{ in.};$ $-20 \text{ in.} \leq y_7 \leq 20 \text{ in.}; 20 \text{ in.} \leq y_8 \leq 60 \text{ in.}$
Material Parameters:	
Density ρ	0.1 (lb/in ³)
Modulus of elasticity E	10^4 (ksi)
Constraints:	
Stress	The allowable elements stress interval: [-25 (ksi), 25 (ksi)]

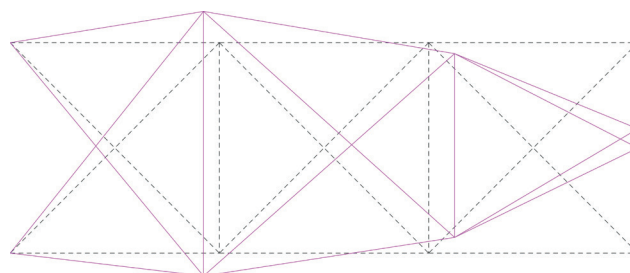


Fig. 3 Optimum layout of the 15-bar planar truss

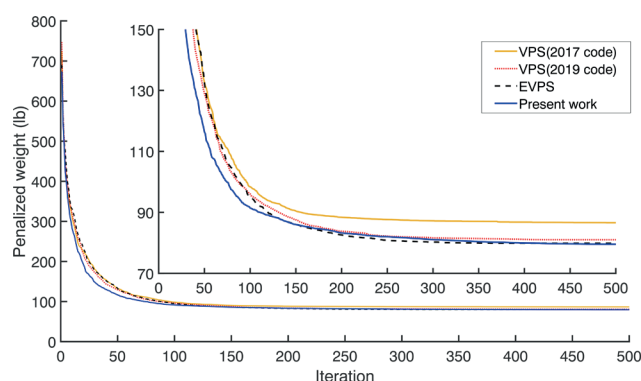


Fig. 4 Convergence curves for the 15-bar planar truss

5.2 The planar 18-bar truss structure

The planar 18-bar truss is at nodes 1, 2, 4, 6 and 8 under vertical loading about 20 kips as shown in Fig. 6. This example has 12 optimization variables that 4 of them are

Table 2 Performance comparison for the 15-bar planar truss

Design variables	GA [15]	iGA [19]	MBRCGA [21]	FM-GA [20]	FA [22]	PSO [23]	CPSO [23]	SCPSO [23]	iPSO [24]	VPS (2017 code) $p = 0.2$	VPS (2019 code) $p = 0.7$	EVPS $p = 0.2$	Present work $\mu_0 = 0.03$
A1	1.174	1.081	0.954	1.081	0.954	0.954	1.174	0.954	1.081	0.954	0.954	1.081	0.954
A2	0.954	0.539	0.539	0.539	0.539	1.081	0.539	0.539	0.539	0.954	0.539	0.539	0.539
A3	0.44	0.287	0.111	0.287	0.22	0.27	0.347	0.27	0.27	0.27	0.27	0.287	0.22
A4	1.333	0.954	0.954	0.954	0.954	1.081	0.954	0.954	0.954	1.081	0.954	0.954	0.954
A5	0.954	0.954	0.539	0.539	0.539	0.539	0.954	0.539	0.539	0.539	0.539	0.539	0.539
A6	0.174	0.22	0.347	0.141	0.22	0.287	0.141	0.174	0.141	0.22	0.22	0.141	0.27
A7	0.44	0.111	0.111	0.111	0.111	0.141	0.141	0.111	0.111	0.111	0.111	0.111	0.111
A8	0.44	0.111	0.111	0.111	0.111	0.111	0.111	0.111	0.111	0.141	0.111	0.111	0.111
A9	1.081	0.287	0.111	0.539	0.287	0.347	1.174	0.287	0.27	1.488	0.954	0.287	0.174
A10	1.333	0.22	0.44	0.44	0.44	0.44	0.141	0.347	0.287	0.347	0.44	0.347	0.44
A11	0.174	0.44	0.44	0.539	0.44	0.27	0.44	0.347	0.44	0.22	0.44	0.44	0.44
A12	0.174	0.44	0.174	0.27	0.22	0.111	0.44	0.22	0.27	0.174	0.141	0.22	0.174
A13	0.347	0.111	0.174	0.22	0.22	0.347	0.141	0.22	0.287	0.44	0.111	0.27	0.174
A14	0.347	0.22	0.347	0.141	0.27	0.44	0.141	0.174	0.174	0.22	0.22	0.141	0.27
A15	0.44	0.347	0.111	0.287	0.22	0.22	0.347	0.27	0.27	0.27	0.27	0.287	0.22
x2	123.189	133.612	105.7835	101.5775	114.967	106.0521	102.2873	137.2216	132.2415	129.1251	139.7080	116.1486	110.8864
x3	231.595	234.752	258.5965	227.9112	247.04	239.0245	240.505	259.9093	257.4379	247.3116	257.5795	251.4127	254.8960
y2	107.189	100.449	133.6284	134.7986	125.919	130.3556	112.584	123.5006	128.3136	116.4325	133.1802	128.9126	137.8297
y3	119.175	104.738	105.0023	128.2206	111.067	114.273	108.0428	110.002	111.2506	104.9919	102.8041	109.2586	113.7671
y4	60.462	73.762	54.4546	54.863	58.298	51.9866	57.7952	59.9356	59.9894	59.4382	56.8942	55.7240	70.9138
y6	-16.728	-10.067	-19.929	-16.4484	-17.564	1.8135	6.4299	-5.1799	-10.5543	-0.2914	-11.2360	-12.9730	-13.0542
y7	15.565	-1.339	3.6223	-13.301	-5.821	9.1827	-1.8006	4.2193	10.7686	-0.6786	10.1297	-9.0125	8.9559
y8	36.645	50.402	54.4474	54.8572	31.465	46.9087	57.7987	57.8829	60	59.4382	56.8942	55.7239	59.9658
Best weight (lb)	120.52	79.82	72.5152	76.6854	75.55	82.2344	77.6153	72.5143	72.7373	78.7876	74.5743	74.8172	73.7463
Average weight (lb)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	76.411	74.316	86.6161	81.0198	79.8588	79.5491
Worst weight (lb)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	80.156	76.522	99.4843	89.6244	85.4333	85.7443
Std. deviation (lb)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1.922	2.023	4.66	3.11	2.32	2.15
No. of analyses	6,000	8,000	10,000	8,000	8,000	4,500	4,500	4,500	4,980	8,840	7,860	9,820	9,940

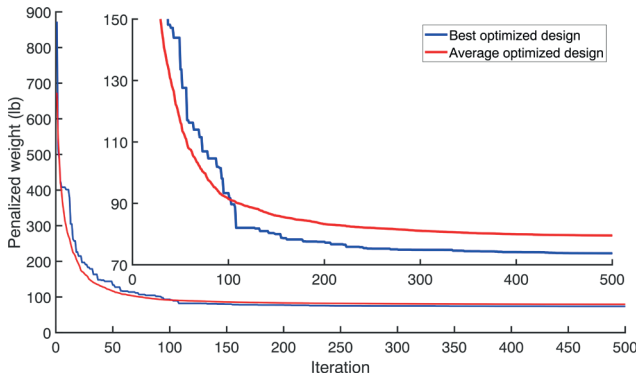


Fig. 5 Convergence curves of the best and average performance of the studied algorithm for the 15-bar planar truss

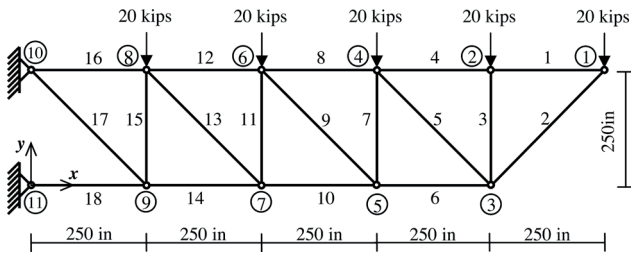


Fig. 6 Schematic of the 18-bar planar truss

in discrete search space which are related to member sections and 8 of them are in continuous search space that are related to node coordinates. Information about modeling and optimization are presented in Table 3.

Table 4 shows that, like the 15-bar truss results, the MBRCGA [21], SCPSO [23] and iPSO [24] algorithms performed better than the present method, but still the best weight obtained by the present method (i.e., 4,525.09 lbs) is better than the values obtained by the VPS algorithm and its enhanced version (EVPS). In addition to the fact that the present method requires more analysis to achieve the best weight than the other two versions of the VPS algorithm, the average and standard deviation for 30 independent runs were also more values. Optimum layout for 18-bar truss is shown in Fig. 7 that found by the present method. Fig. 8 shows a comparison between the convergence history of VPS, EVPS algorithms and the present method for the average performance of the algorithms in 30 independent runs. The convergence history of the present method for the mean and best performance of the algorithm in 30 independent runs are shown in Fig. 9.

5.3 The spatial 25-bar truss

As shown in Fig. 10 the 25-bar truss is considered as the third problem. This structure is under concentrated loading as shown in Table 5. This example consists of 13

Table 3 Modeling and design data for the 18-bar planar truss

Simulation and design data	
Design variables:	
Sizing variables	$A_1 = A_4 = A_8 = A_{12} = A_{16},$
	$A_2 = A_6 = A_{10} = A_{14} = A_{18},$
	$A_3 = A_7 = A_{11} = A_{15},$
	$A_5 = A_9 = A_{13} = A_{17}.$
Layout variables	$x_3, x_5, x_7, x_9, y_3, y_5, y_7, y_9.$
Search range:	
Possible sizing variables	$A_i \in S = \{2.00, 2.25, 2.50, \dots, 21.25, 21.50, 21.75\} (in^2)$
Layout variables bounds	$775 \text{ in.} \leq x_3 \leq 1225 \text{ in.};$
	$525 \text{ in.} \leq x_5 \leq 975 \text{ in.};$
	$275 \text{ in.} \leq x_7 \leq 725 \text{ in.};$
	$25 \text{ in.} \leq x_9 \leq 475 \text{ in.};$
Material Parameters:	
Density ρ	0.1 (lb/in ³)
Modulus of elasticity E	10^4 (ksi)
Constraints:	
Stress	The allowable elements stress interval: [-25 (ksi), 25 (ksi)]
Local buckling	$ \sigma_c _i \leq \frac{\beta E A_i}{l_i^2}, \quad i = 1, 2, \dots, 18, \quad \beta = 4$

variables that 8 of them are in discrete search space for sizing optimization and the rest are in continuous search space for layout optimization. Other information related to modeling and optimization are given in Table 5.

According to the results shown in Table 6, VPS algorithm, SCPSO [23] and iPSO [24] found a smaller weight as the best weight, which had better results than the present method, while the present method has achieved less weight compared to the EVPS algorithm. Comparison between the optimum layout obtained by the present method and initial layout is shown in Fig. 11. Comparison of the average performance of VPS, EVPS algorithms and the present method for 30 independent runs are shown in Fig. 12. The convergence history of the present method for the mean and best performance of the algorithm in 30 independent runs are shown in Fig. 13.

5.4 The planar 47-bar truss

The last sizing and shape optimization problem is the planar 47-bar truss that is indicated in Fig. 14 which consist 47 members and 22 nodes. The nodes of structure are subjected to three load cases that are presented in Table 7. This example has 44 optimization variables that 27 of them are in discrete search space which are related to member sections and 17 of them are in continuous search space that are

Table 4 Performance comparison for the 18-bar planar truss

Design variables	SA [17]	FM-GA [18]	MBRCGA [21]	FM-GA [20]	PSO [23]	CPSO [23]	SCPSO [23]	iPSO [24]	VPS (2017 code) $p = 0.2$	VPS (2019 code) $p = 0.2$	EVPS $p = 0.2$	Present Work $\mu_0 = 0.03$
A1	12.25	12.25	12.75	12.75	12	12	12.5	14.25	13	11.75	12.25	12
A2	17.5	18	18.25	18.5	18.5	17.25	17.5	11.75	16.75	18.25	18	18
A3	5.75	5.25	5	4.75	5.25	6.25	5.75	6	7.25	5.25	5.25	5
A5	4.25	4.25	3.25	3.25	4.5	4.75	3.75	8	3.5	5	4.25	4.5
x3	910	913	916.0812	917.4475	903.9806	902.9141	907.2491	916.4975	895.9864	930.8557	916.2911	918.1752
y3	179	186.8	191.43	193.7899	185.7807	174.7201	179.8671	190.5241	162.2994	188.6362	189.8249	190.8539
x5	638	650	650.0573	654.3243	644.917	632.7129	636.7873	916.4975	616.1673	661.1871	650.3419	651.8908
y5	141	150.5	153.4968	159.9436	144.9692	141.2956	141.8271	152.9217	124.1998	147.9244	150.7933	149.8333
x7	408	418.8	419.4508	424.4821	428.2196	407.1323	407.9442	649.4695	390.8926	422.3898	419.3627	420.0147
y7	91	97.4	105.5322	108.5779	100.5623	85.9332	94.0559	105.425	86.0397	93.9783	98.9555	97.9757
x9	198	204.8	205.6591	208.4691	209.5415	197.672	198.7897	205.4255	188.8596	209.3734	205.0683	205.5626
y9	24	26.7	36.4848	37.6349	24.3748	19.8093	29.5157	36.4252	33.9445	18.5291	27.5897	23.1446
Best weight (lb)	4533.24	4547.9	4520.2	4530.7	4609.001	4561.131	4512.365	4520.99	4,595.53	4,600.02	4,544.25	4,525.09
Average weight (lb)	N/A	N/A	N/A	N/A	N/A	N/A	4551.709	4526.585	4,978.03	4,769.76	4,743.40	4,798.26
Worst weight (lb)	N/A	N/A	N/A	N/A	N/A	N/A	4621.227	4560.27	5,747.31	4,993.75	5,112.79	5,147.76
Std. deviation (lb)	N/A	N/A	N/A	N/A	N/A	N/A	37.691	14.889	244.24	89.16	133.33	169.86
No. of analyses	N/A	N/A	10,000	N/A	4,500	4,500	4,500	4,450	8,300	9,780	9,400	10,000

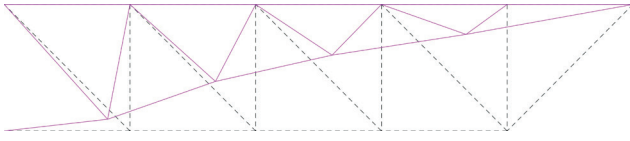


Fig. 7 Optimum layout of the 18-bar planar truss

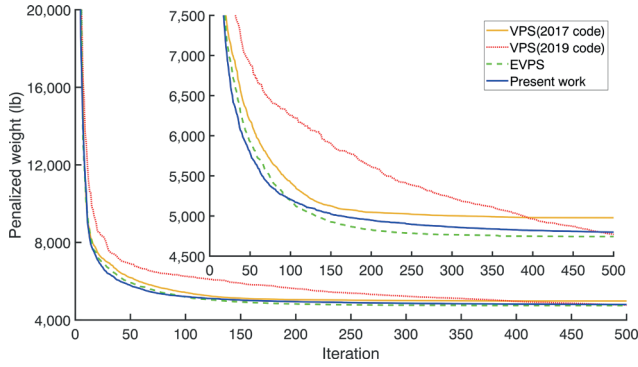


Fig. 8 Convergence curves for the 18-bar planar truss

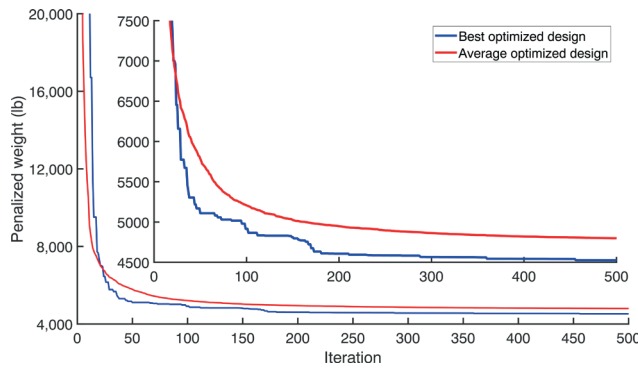


Fig. 9 Convergence curves of the best and average performance of the studied algorithm for the 18-bar planar truss

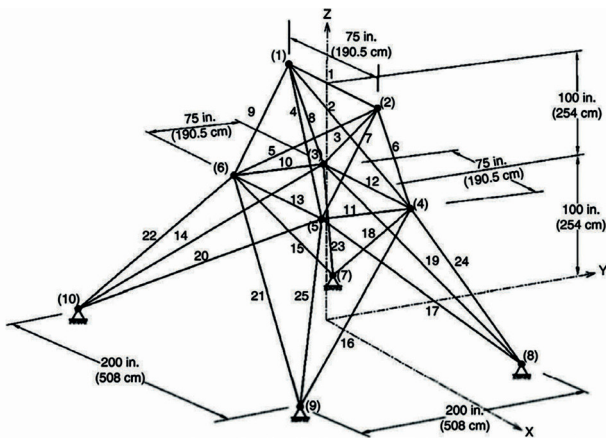


Fig. 10 Schematic of the 25-bar spatial truss

related to node coordinates. Other information for modeling and optimization are given in Table 7.

According to the results of Table 8, the SA [17], FSD-GWADE [25], CPSO [23], SCPSO [23] and iPSO [24] algorithms have better results than the present method, but the best and average weights for 30 independent

Table 5 Modeling and design data for the 25-bar spatial truss

Simulation and design data			
design variables:			
Sizing variables	$A_1; A_2 = A_3 = A_4 = A_5; A_6 = A_7 = A_8 = A_9;$		
	$A_{10} = A_{11}; A_{12} = A_{13}; A_{14} = A_{15} = A_{16} = A_{17};$		
Layout variables	$A_{18} = A_{19} = A_{20} = A_{21}; A_{22} = A_{23} = A_{24} = A_{25};$		
	$x_4 = x_5 = -x_3 = -x_6; x_8 = x_9 = -x_7 = -x_{10};$		
	$y_3 = y_4 = -y_5 = -y_6; y_7 = y_8 = -y_9 = -y_{10};$		
	$z_3 = z_4 = z_5 = z_6;$		
Search range:			
Possible sizing variables	$A_i \in S = \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2.0, 2.1, 2.2, 2.3, 2.4, 2.5, 2.6, 2.8, 3.0, 3.2, 3.4\}(in^2).$		
Layout variables bounds	$20\ in. \leq x_4 \leq 60\ in.; 40\ in. \leq x_8 \leq 80\ in.;$ $40\ in. \leq y_4 \leq 80\ in.; 100\ in. \leq y_8 \leq 140\ in.;$ $90\ in. \leq z_4 \leq 130\ in.$		
Material Parameters:			
Density ρ	0.1 (lb/in ³)		
Modulus of elasticity E	10 ⁴ (ksi)		
Constraints:			
Stress	The allowable elements stress interval: [-40 (ksi), 40 (ksi)]		
Displacement	The allowable nodal displacement interval: [-0.35 (in.), 0.35 (in.)]		
Loads:			
Nodes	F_x (kips)	F_y (kips)	F_z (kips)
1	1.0	-10.0	-10.0
2	0.0	-10.0	-10.0
3	0.5	0.0	0.0
6	0.6	0.0	0.0

runs found by the present method is better than VPS and EVPS algorithms, but the number of analyzes is more. Comparison between the optimum layout obtained by the present method and initial layout is shown in Fig. 15. Fig. 16 shows the comparison of convergence histories of the 47-bar truss structure for VPS, EVPS and the present method. Fig. 17 is compared the convergence histories of average and best performance for the present method.

6 Conclusions

In present paper, the ability of the new enhanced version of VPS metaheuristic algorithm that is named Improved Vibrating Particles System (IVPS) algorithm in optimizing size/layout the truss structures is investigated. VPS is a multi agent-based algorithm by inspiration of the free vibration of viscous-damped systems with single degree of freedom. The present method has tried to reduce the dependence of the VPS algorithm on its regulatory parameters by weighting the regulatory parameters of the VPS algorithm using the objective function values.

Table 6 Performance comparison for the 25-bar spatial truss

Design variables	GA [15]	iGA [19]	FM-GA [18]	FA [22]	FM-GA [20]	PSO [23]	CPSO [23]	SCPSO [23]	iPSO [24]	VPS (2017 code) $p = 0.2$	VPS (2019 code) $p = 0.2$	EVPS $p = 0.2$	Present Work $\mu_0 = 0.03$
A1	0.1	0.1	0.1	0.1	0.1	0.1	0.3	0.1	0.1	0.1	0.1	0.1	0.1
A2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
A6	1.1	1.1	1.1	0.9	1.1	1.1	1	1	1	1	1	0.9	1
A10	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
A12	0.3	0.1	0.1	0.1	0.1	0.4	0.1	0.1	0.1	0.1	0.1	0.1	0.1
A14	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
A18	0.2	0.2	0.1	0.1	0.2	0.4	0.2	0.1	0.1	0.1	0.1	0.2	0.1
A22	0.9	0.7	1	1	0.8	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9
x4	41.07	35.47	36.23	37.32	33.0487	27.6169	33.4976	36.952	37.6	37.6171	37.6475	32.6972	37.5279
y4	53.47	60.37	58.56	55.74	53.5663	51.6196	62.3735	54.579	54.46	54.4361	54.4454	53.4719	54.8148
z4	124.6	129.07	115.59	126.62	129.9092	129.9071	114.5945	129.976	130	130.0000	129.9998	129.4781	129.4257
x8	50.8	45.06	46.46	50.14	43.7826	42.5526	40.0531	51.732	51.89	51.8914	51.8893	43.2422	51.7433
y8	131.48	137.04	127.95	136.4	136.8381	132.7241	133.6695	139.532	139.55	139.5491	139.5388	137.4310	139.5783
Best weight (lb)	136.2	124.94	124	118.83	120.1149	129.2076	123.451	117.227	117.255	117.2556	117.2556	119.3020	117.2900
Average weight (lb)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	122.876	119.57	123.4255	118.6200	124.1990	121.8993
Worst weight (lb)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	132.672	121.969	144.7848	122.4392	137.6314	126.8062
Std. deviation (lb)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	3.671	1.3908	5.62	1.34	3.92	2.32
No. of analyses	N/A	6,000	N/A	6,000	10,000	4,500	4,500	4500	4870	5,840	9,360	5,080	9,120

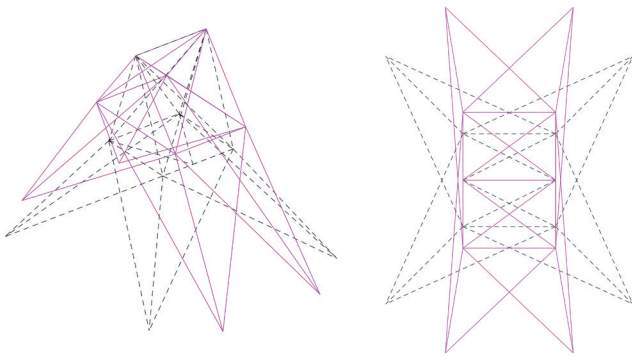


Fig. 11 Optimum layout of the 25-bar spatial truss

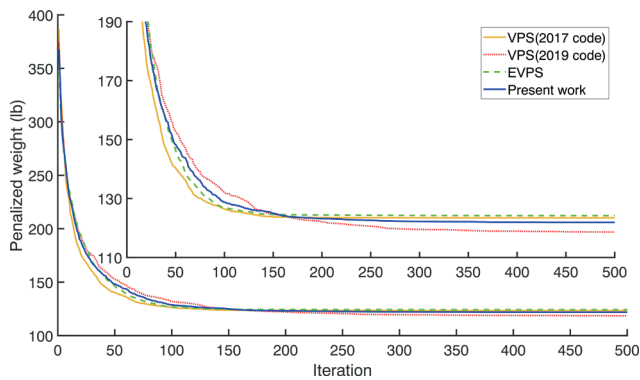


Fig. 12 Convergence curves for the 25-bar spatial truss

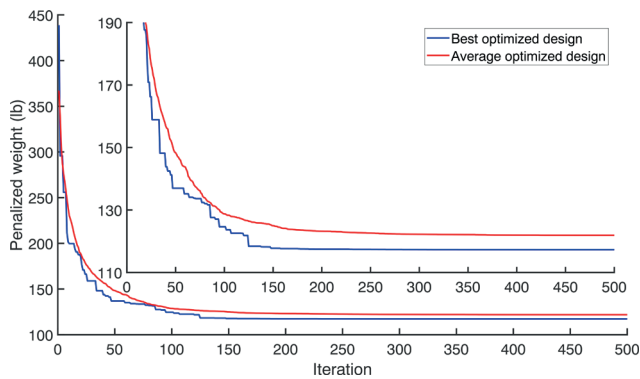


Fig. 13 Convergence curves of the best and average performance of the studied algorithm for the 25-bar spatial truss

All of the optimization problems of truss structure in this paper involve size and layout variables and the fourth problem with 44 optimization variables is a slightly larger scale problem. The results of the present method in all problems were close to the best results obtained by other powerful algorithms and in some cases, it achieved better results than them. Also, in all structures except 25-bar spatial truss, it has achieved better results than other versions of the vibrating particle system algorithm. The weight gained by the standard version of the vibrating particle system algorithm was slightly different (0.029%)

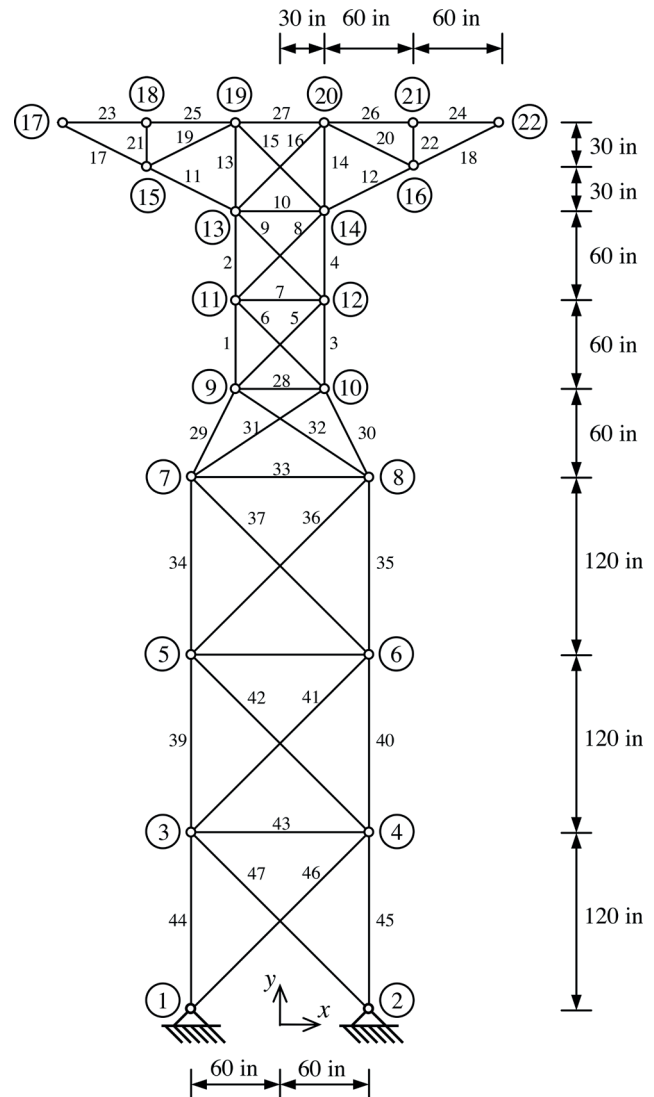


Fig. 14 Schematic of the 47-bar planar truss

from the current method for the spatial 25-bar truss. In this paper, only four small size/layout optimization truss structures have been used to evaluate the capability of present method, so the comparison between the performance of the present method and other versions of the vibrating particle system algorithm can be tested using other benchmark structures.

Compliance with ethical standards

Conflict of interest: No potential conflict of interest was reported by the authors.

Table 7 Modeling and design data for the 47-bar planar truss

Simulation and design data			
Design variables:			
Sizing variables	$A_1 = A_3; A_2 = A_4; A_5 = A_6; A_7; A_8 = A_9; A_{10}; A_{11} = A_{12}; A_{13} = A_{14}; A_{15} = A_{16};$ $A_{17} = A_{18}; A_{19} = A_{20}; A_{21} = A_{22}; A_{23} = A_{24}; A_{25} = A_{26}; A_{27}; A_{28}; A_{29} = A_{30};$ $A_{31} = A_{32}; A_{33}; A_{34} = A_{35}; A_{36} = A_{37}; A_{38}; A_{39} = A_{40}; A_{41} = A_{42}; A_{43}; A_{44} = A_{45};$ $A_{46} = A_{47}$		
	Layout variables $x_1 = -x_2; x_3 = -x_4; y_3 = y_4; x_5 = -x_6; y_5 = y_6; x_7 = -x_8; y_7 = y_8; x_9 = -x_{10};$ $y_9 = y_{10}; x_{11} = -x_{12}; y_{11} = y_{12}; x_{13} = -x_{14}; y_{13} = y_{14}; x_{19} = -x_{20}; y_{19} = y_{20}; x_{18} = -x_{21};$ $y_{18} = y_{21}$		
Search range:			
Possible sizing variables	$A_i \in S=\{0.1, 0.2, 0.3, 0.4, \dots, 4.8, 4.9, 5.0\}(in^2).$		
Layout variables bounds	$0\ in.\leq x_i\leq 120\ in., (i=2, 4, 6, 8); -30\ in.\leq x_i\leq 90\ in., (i=10, 12, 14, 20);$ $30\ in.\leq x_{21}\leq 150\ in.; 60\ in.\leq y_4\leq 180\ in.; 180\ in.\leq y_6\leq 300\ in.;$ $300\ in.\leq y_8\leq 420\ in.; 360\ in.\leq y_{10}\leq 480\ in.; 420\ in.\leq y_{12}\leq 540\ in.; 480\ in.$ $\leq y_{14}\leq 600\ in.; 540\ in.\leq y_{20}\leq 660\ in.; 540\ in.\leq y_{21}\leq 660\ in.$		
	Material Parameters:		
Density ρ	0.3 (lb/in ³)		
Modulus of elasticity E	3×10^4 (ksi)		
Constraints:			
Stress	The allowable elements stress interval: [-15 (ksi), 20 (ksi)]		
Local buckling	$\left (\sigma_c)_i\right \leq \frac{\beta EA_i}{l_i^2},\ i=1,2,\dots,47,\ \beta=3.96.$		
Loads:			
case	Nodes	F_x (kips)	F_y (kips)
1	17	6.0	-14.0
	22	6.0	-14.0
2	17	6.0	-14.0
3	22	6.0	-14.0

Table 8 Performance comparison for the 47-bar planar truss

Design variables	IGA [16]	SA [17]	FSD-GWADE [25]	PSO [23]	CPSO [23]	SCPSO [23]	iPSO [24]	VPS (2017 code) $p = 0.2$	VPS (2019 code) $p = 0.2$	EVPS $p = 0.2$	Present Work $\mu_0 = 0.02$
A3	2.5	2.5	2.7	2.8	2.6	2.5	2.5	0.6	4.5	2.7	2.9
A4	2.2	2.5	2.6	2.7	2.5	2.5	2.5	0.9	3	2.4	2.6
A5	0.7	0.8	0.7	0.8	0.7	0.8	0.8	3.8	1	0.8	0.8
A7	0.1	0.1	0.1	1.1	0.3	0.1	0.1	0.1	0.2	0.3	0.1
A8	1.3	0.7	0.8	0.8	1.2	0.7	0.7	3.8	1.2	1.1	1.3
A10	1.3	1.3	1.2	1.3	1.1	1.4	1.4	1.3	1	1.3	1
A12	1.8	1.8	1.7	1.8	1.6	1.7	1.7	2.1	2	2	1.9
A14	0.5	0.7	0.8	0.9	0.8	0.8	0.8	0.9	1.7	0.5	0.6
A15	0.8	0.9	0.9	1.2	1.1	0.9	0.9	1.6	0.9	0.8	0.8
A18	1.2	1.2	1.3	1.4	1.3	1.3	1.3	1.5	2.4	1.7	1.4
A20	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.9	0.6	0.6	0.3
A22	1.2	1.3	1	1.4	0.8	0.9	0.9	1.4	1.4	0.9	1
A24	0.9	0.9	1	1.1	1	1	1	1.1	1	1.3	1.1
A26	1	0.9	1	1.2	1	1.1	1.1	1	0.7	1.4	1.1
A27	3.6	0.7	0.9	1.6	0.9	5	0.9	1.4	0.9	1.2	0.9
A28	0.1	0.1	0.1	1	0.1	0.1	0.1	0.2	0.4	0.3	0.1
A30	2.4	2.5	2.6	2.8	2.7	2.5	2.5	3.3	3	2.6	2.6
A31	1.1	1	0.9	0.8	0.9	1	1	1	1.1	1	0.9
A33	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1.5	0.3	0.1	0.1
A35	2.7	2.9	2.8	3	3	2.8	2.8	3.3	3.2	2.6	2.8
A36	0.8	0.8	1.1	0.9	1	0.9	0.9	1.2	1.2	1.1	1
A38	0.1	0.1	0.1	0.1	0.2	0.1	0.1	1.7	0.1	0.2	0.1
A40	2.8	3	3	3.3	3.3	3	3	3.6	3.2	2.7	3.1
A41	1.3	1.2	1.1	0.9	0.9	1	1	1.6	1.4	1.3	1
A43	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.9	0.3	0.1	0.1
A45	3	3.2	3.1	3.3	3.3	3.2	3.2	4.5	3.3	3	3.3
A46	1.2	1.1	1.1	1.2	1.1	1.2	1.2	0.8	1.3	1.2	1.3
x2	114	104	109.61	98.8628	99.363	101.3393	101.2077	76.8274	102.9225	115.9306	95.5386
x4	97	87	93.078	78.6595	83.4439	85.9111	85.8555	67.3946	78.7688	103.3133	80.5830
y4	125	128	126.65	146.7331	126.3845	135.9645	135.9679	86.1660	145.3218	114.5742	142.8836
x6	76	70	70.752	66.5231	69.5148	74.7969	74.9087	62.8919	64.4627	84.3044	69.8276
y6	261	259	246.32	239.0901	218.2013	237.7447	238.0442	215.7321	271.2362	255.6127	253.0915

Continuing Table 8

Design variables	IGA [16]	SA [17]	FSD-GWADE [25]	PSO [23]	CPSO [23]	SCPSO [23]	iPSO [24]	VPS (2017 code) $p = 0.2$	VPS (2019 code) $p = 0.2$	EVPS $p = 0.2$	Present Work $\mu_o = 0.02$
x8	69	62	56.172	55.6936	58.0004	64.3115	64.1206	47.7076	45.9873	64.5654	57.6594
y8	316	326	356.26	327.7882	322.2272	321.3416	321.5037	343.3780	364.9041	359.9130	347.4688
x10	56	53	48.498	48.8641	51.4015	53.3345	53.3481	34.4688	42.6528	45.7518	49.0938
y10	414	412	436.37	398.6775	401.5626	414.3025	413.7265	419.6109	443.0305	432.0751	436.6117
x12	50	47	42.37	43.14	46.8605	46.0277	46.2881	-28.2689	43.9389	41.9274	37.0847
y12	463	486	490.66	464.7831	458.3021	489.9216	487.9695	465.6604	457.9637	486.7322	483.2620
x14	54	45	41.61	37.8993	46.8885	41.8353	41.8603	30.6771	49.3600	49.9330	47.8346
y14	524	504	521.04	511.045	527.8575	522.4161	522.8897	505.6582	518.5287	526.3668	524.8298
x20	1	2	1.4026	18.2341	16.2354	1.0005	0.9892	4.6435	-10.8026	-1.4316	7.1034
y20	587	584	597.36	594.071	610.8496	598.3905	598.3959	583.2983	602.5850	580.6381	588.9739
x21	99	89	95.312	90.9369	98.3239	97.8696	97.8656	80.4288	82.0523	90.4552	92.5254
y21	631	637	625.99	621.3943	624.958	624.055	624.0605	623.6525	656.6469	609.6711	620.7568
Best weight (lb)	1925.79	1871.7	1871.7	1975.84	1908.83	1864.1	1861.429	2,297.8011	2,283.0965	1,998.2013	1,911.7774
Average weight (lb)	N/A	N/A	1884.16	N/A	N/A	1894.056	1873.011	2,693.6165	2,736.9421	2,098.9179	2,070.6756
Worst weight (lb)	N/A	N/A	1899.7	N/A	N/A	2007.563	1908.991	3,120.5369	3,281.0248	2,321.7244	2,425.9799
Std. deviation (lb)	N/A	N/A	7.77	N/A	N/A	34.755	20.782	222.85	243.15	83.58	110.69
No. of analyses	100,000	N/A	187,488	25,000	25,000	25,000	20,040	30,000	29,840	29,600	30,000

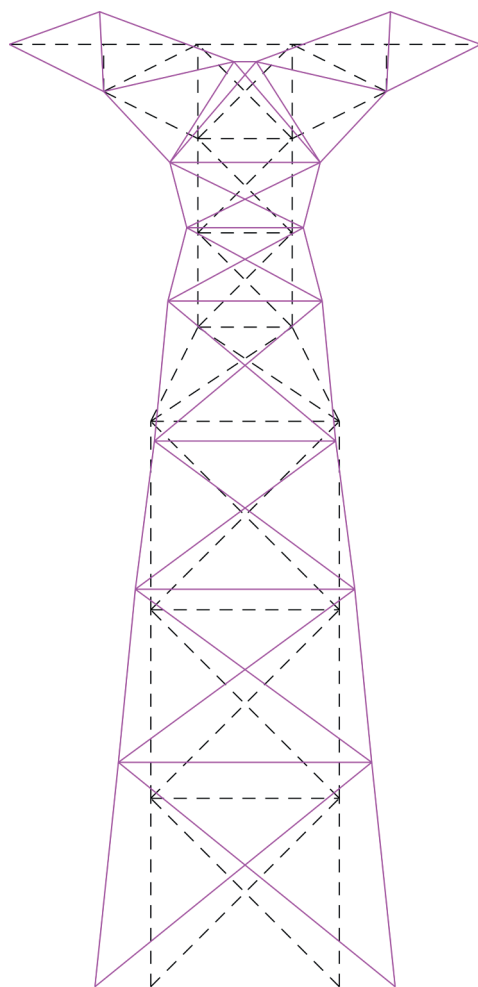


Fig. 15 Optimum layout of the 47-bar planar truss

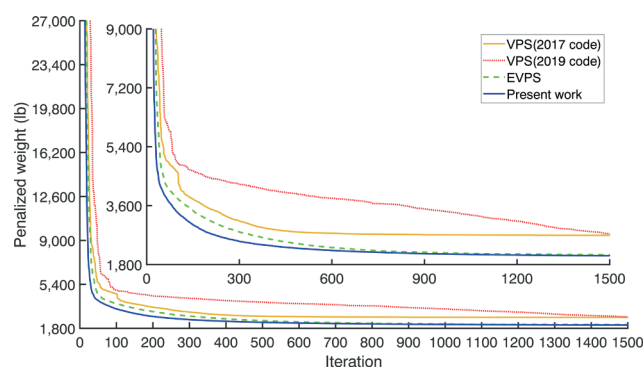


Fig. 16 Convergence curves for the 47-bar planar truss

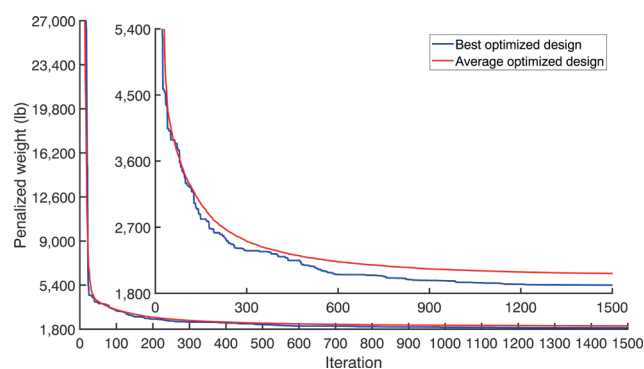


Fig. 17 Convergence curves of the best and average performance of the studied algorithm for the 47-bar planar truss

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